An improved decision model for evaluating risks in construction projects

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Abstract

The paper develops an innovative risk evaluation methodology to address the challenges of multi-criteria decision-making problem of project evaluation and selection. The methodology considers Fuzzy Analytic Network Process (FANP) to incorporate the inter-dependencies of different risk factors, and Failure Mode and Effect Analysis to conduct the rating analysis of projects to develop the decision matrix. Finally, evaluation based on the distance from average solution compares alternative projects and reports the optimal solution. The proposed approach allows project managers to engage in the evaluation process and to use fuzzy linguistic values in the assessment process. A case study from the construction sector is selected to verify the efficacy of the proposed approach over other popular approaches in literature.

Keywords: Multi-criteria decisions; Failure mode and effect analysis; Fuzzy analytical network process; Risk assessment; Construction projects.

Introduction

In industrial projects, the risk assessment exercise has strategic importance, and can decide the success or failure of the project. Risk assessment involves the analysis of the whole project in order to reduce the impact of potential risk factors. It begins by identifying the potential risks that could influence the project. During the project planning phase, the project manager usually forms a team of experts and relevant stakeholders to assess the potential risk factors that could affect the successful completion of the project. The team uses techniques like brainstorming, discussions and tools such as flowcharts, root cause analysis, histogram and cause-effect analysis to release potential problems. Several tools are utilized by different risk management teams to develop the risk-breakdown structure and risk-profile. This paper is primarily focused on the risk evaluation and assessment of construction projects.

Scenario analysis is one of the most popularly used techniques for evaluating project risks. The project team evaluates the impact of each risk factor in terms of the probability of its occurrence and the influence on the project. A structured approach is needed to recognize potential / known failure modes at different levels of the project and investigate the effect on the next sub-system level (Sharma et al. 2005). Failure Mode and Effect Analysis (FMEA) is considered as a fundamental tool and a part of the risk assessment methodology in several studies, and is established as one of the most reliable techniques (Dinmohammadi and Shafiee, 2013). This technique can help in understanding different failure modes within a system, evaluating their impacts, and deciding for corrective actions (Abdelgawad and Fayek, 2010). However, reported applications of this technique in the construction industry are limited (Andery et al., 2000; Nielsen, 2002). Evaluating different risk factors in construction projects is a complex task since the objective functions may change during the project life cycle (Dikmen et al. 2008). Further, Tserng et al. (2009) discussed an ontology based risk management framework for construction projects based on the project life cycle variance and covariance. However, FMEA provides a better approach to assess the severity of a potential risk, and by identifying the "risk priority" of a project, the key stakeholders can adopt a suitable risk management strategy to manage potential risks (Safari et al. 2016). In practice, it is necessary to address technical, external and internal (organizational) issues through a risk breakdown structure. When developing this structure, it is important to reduce the chance of a risk event being missed, and to develop a comprehensive view of the project.

Research significance

Multi-criteria decision-making (MCDM) techniques are amongst the most efficient approaches to evaluate risk factors and assist in real-life decision problems. In recent years, there is growing trend in integrating different MCDM approaches to develop hybrid techniques with better performance to address risk assessment problems in different projects (Chan and Kumar 2007; Chan et al. 2008; Chang 2013; Prakash and Barua, 2016). It enables experts to be flexible in choosing relevant methods and creating integrated structures. Past literature (such as Gu and Zhu 2006; Tzeng et al. 2007; Yang and Tzeng, 2011; Liu et al. 2012; Liu et al. 2013) have provided further evidence to support the novelty of integrated and hybrid methods in order to take the advantage of two or more decision making approaches.

Moreover, Franceschini and Galetto (2001) presented a multi-expert MCDM model to analyze the risk preferences of failures in FMEA. In this model, risk factors were transformed as evaluation criteria, while failure modes were considered as different alternatives to be decided. This method contemplated each decision-making criterion as a fuzzy subset over the set of alternatives. Chin et al. (2009) discussed a FMEA model using the group-based evidential reasoning (ER) approach to collate diverse opinions and prioritize failure modes under uncertainties such as incomplete assessment, ignorance and intervals. Hu et al. (2009) developed a green component risk priority number to analyze the risks involved due to hazardous substances. In their study, Fuzzy analytic hierarchy process (FAHP) was used to identify the relative weights of risk factors. Then the green component risk priority number (RPN) was calculated for each component to assess the risks derived from them. In this study, the application of fuzzy value FMEA in the context of risk evaluation is discussed, where FMEA forms an initial decision matrix for evaluation process.

The novelty of the proposed approach lies in the way it analyzes the anatomy of a project framework. One of the important activities in decision modelling is to find logical ways to weigh different decision attributes. In past literature, mostly Analytic hierarchy process (AHP), Delphi and entropy based approaches are used to determine the weights of different influencing factors. However, in many decision problems, the decision criteria are strictly dependent on each other. Analytic network process (ANP) is the method that undertakes the interrelationship of risk factors in a ratio scale and aids in overcoming the drawbacks of the decision levels and clusters (Tavana et al. 2016). The advantages of ANP can be summarized as follows (Ignatius et al. 2016) : 1) ANP converts qualitative values into numerical values for relative analysis of preferences, 2) It has a simple and intuitive structure, and 3) it allows the participation of stakeholders and experts in the decision process.

In addition, risk evaluation in real life problems usually confronts low levels of information and certainty. In the literature, the *fuzzy approach* is recognized as an effective tool for tackling uncertainty stemming from inaccurate information (Wang et al. 2009). In multi-criteria decision-making problems, where some of the criteria cannot be quantitatively represented, the fuzzy set theory can be helpful to enable project assessors to express their linguistic preferences, and to convert those preferences into numerical values for comparative analysis (Ho et al. 2012). He et al. (2015) studied the complexity of mega construction projects in China using Fuzzy ANP methodology and argued that the methodology can help decision makers to develop effective strategy for the project execution.

In this paper, an integrated decision-making approach, combining ANP and FMEA in a fuzzy environment is proposed for the risk evaluation process. Very limited studies are available in the literature which attempt to integrate FMEA and ANP with fuzzy variables for risk assessment. Additionally, the 'evaluation based on the distance from the average solution' (EDAS) method is adopted to compare alternative projects and rank them based on risk priority. A case study is also discussed to explain the implementation process of the proposed approach.

The rest of the paper is organized as follows: Next section discusses the proposed integrated approach (combining fuzzy set theory, ANP and FMEA) for risk assessment. Further, the case study and risk management methodology are presented, along with the analysis and findings. The managerial implications of the proposed approach is also discussed. At the end, paper concludes with a discussion on future research directions.

Research Background

This section discusses different methods for addressing multi-criteria decision-making problems. Particular attention has been given to approaches that are closely related to the integrated approach for risk evaluation proposed in this paper.

Fuzzy set theory

In real world decision problems, there are many instances where decision makers are faced with multiple criteria when reaching to a decision. However, estimating the impact of these criteria on potential decision outcomes is cumbersome, and this sometimes results in extremely pessimistic or optimistic decisions being made. In every decision environment two types of systems can be proposed based on the availability of information. In white systems, all internal information is completely known, whereas in a black system, it is difficult to obtain any information and characteristics about the system (Zavadskas et al. 2010). Saaty (1980) introduced the analytic hierarchy process (AHP) to accurately represent the consensus of experts and is one of the most widely applied methods in practical applications. In his study, the geometric mean is used as the reference for triangular fuzzy numbers. Zadeh (1965) provided the fuzzy set theory for dealing with the uncertainty due to imprecise and vague information. The theory also allows mathematical operations and programming to be applied in the fuzzy domain. A fuzzy set is a class of objects with a continuum of grades of membership (degree of compatibility) (Peng and Selvachandran 2017). Such a set is characterized by a membership function, which reflects the degree of compatibility assigned to each object with the grade of membership between 0 and 1.

A triangular fuzzy number (TFN) is defined simply as (l, m, u) where parameters l, m, and u represent the smallest possible value, the most promising value and the largest possible value that denotes a fuzzy event. The triangular fuzzy numbers $\tilde{a}_{ij}$ can be established as:

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \tag{1}$$

$$l_{ij} \le m_{ij} \le u_{ij},\ l_{ij}, m_{ij}, u_{ij} \in (0,1) \tag{2}$$

To establish the fuzzy pair-wise comparison matrix, the following procedure must be followed:

Suppose $\tilde{A} = [\tilde{a}_{ij}]$ denotes a triangular fuzzy number for depicting the relative importance of criteria C_1, C_2,….C_n. In this way, $\tilde{a}_{ij}$ represents a matrix constructed by triangular fuzzy numbers.

$$\tilde{A} = [\tilde{a}_{ij}] = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \frac{1}{\tilde{a}_{12}} & 1 & & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{\tilde{a}_{1n}} & \frac{1}{\tilde{a}_{2n}} & \cdots & 1 \end{bmatrix} \tag{3}$$

Defuzzification is a technique to convert the fuzzy number into crisp real numbers and the procedure of defuzzification is to locate the Best Non-fuzzy Performance (BNP) value (Tsaur and Wang 2007). Methods such as the Mean-of-Maximum, the Centre-of-Area, and the α-cut method are the most common defuzzification approaches. In this research, fuzzy risk criteria are defuzzified with the help of the Centre-of-Area method. This was chosen due to its simplicity and its less reliance on the personal judgement of analysts. A defuzzified value of a TFN can be produced using the equation below:

$$\text{BNP} = [(U_{ij} - L_{ij}) + (M_{ij} - L_{ij})]/3 + L_{ij} \tag{4}$$

Fuzzy ANP

ANP is a popular MCDM technique useful to deal with interdependency of complex decision factors. It helps decision makers (DMs) to define complex relationships among several decision levels and their corresponding attributes (Saaty 1996). It helps in overcoming the drawbacks of AHP in addressing interrelationships issues among different decision levels using a super-matrix which detects the composite weights (Shyur, 2006; Kang et al. 2012).

By structuring the problem as an ANP model, the uncertain vague elements of matrix A used for pair-wise comparisons can be redefined by fuzzy membership functions reflecting the degree of compatibility for both the quantitative and the qualitative criteria. By pair-wise comparisons using a fuzzy membership function e.g. with triangular fuzzy numbers, the fuzzy pair-wise comparison matrix $\tilde{A}$ with elements $\tilde{a}_{ij}$, is constructed where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ reflects the influence of element i over element j that could be a criterion/alternative in the network with lower (l_{ij}), mean (m_{ij}) and higher u_{ij} values respectively. The value $u_{ij} - l_{ij}$ could reflect the domain/degree of fuzziness. The greater that $u_{ij} - l_{ij}$ is, the fuzzier the degree is. When $u_{ij} - l_{ij} = 0$, the judgment is a non-fuzzy number (crisp value) with m_{ij} importance value. Contrarily, assuming that $\tilde{A}$ is a positive n × n reciprocal matrix, $\tilde{a}_{ij} = \tilde{a}_{ij}^{-1} = (\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}})$ that represents influence of element *j* over element *i* with lower $\frac{1}{u_{ij}}$, mean $\frac{1}{m_{ij}}$, and higher $\frac{1}{l_{ij}}$ values respectively. As a result, the fuzzification increases the complexity of the computation for synthesis judgments based on the fuzzy elements $a_{ij}s$ .To be able to evaluate a fuzzy ANP model through standard pair-wise comparisons, the fuzzy values are standardized into a single-pattern fuzzy set dealing with both linguistic and/or quantifiable criteria (Abdi, 2009). Accordingly, the importance weights are defined with five triangular fuzzy sets: $\hat{1}, \hat{3}, \hat{5}, \hat{7}, \hat{9}$ with their corresponding lower, mean, and upper values defined in equation (5) and represented in **Table 1** (Abdi and Labib, 2004).

$$\tilde{a}_{ji} = \begin{cases} \hat{1} & ; \in (1, 1, 3) \\ \hat{x} & ; \in (x-2, x, x+2) \\ \hat{9} & ; \in (7, 9, 9) \end{cases} \quad (5)$$

<< Insert Table 1 about here >>

The fuzzy range of ($\hat{1}, \hat{3}, \hat{5}, \hat{7}, \hat{9}$) are used to express linguistic preferences for evaluation criteria in terms of Equal (EQ), Low (L), Medium (M), High (H), and Very High (VH) as decision linguistic variables (**Table 1**), respectively. EQ can also represent equal to very low importance. If criterion (c_i) is assigned one of the fuzzy numbers above when compared with criterion (c_j), then c_j has the reciprocal value when compared with c_i. To simplify the weighting process, the priority values are put in a reciprocal comparison bar for each pair of attributes with respect to a criterion/alternative. For example, if value 5 is assigned on the right-hand side criterion (c_j), then criterion c_j is more important than c_i with a moderate degree. Similarly, if value 5 is assigned on the left criterion (c_i), then the criterion c_i is more important than c_j with a moderate degree (Abdi and Labib, 2004).

The synthesized fuzzy degree of criterion i influenced by criterion j, where $i, j = 1,2,\ldots.,n$, each with a triangular fuzzy number $\tilde{a}_{ij}$ in an ANP structure, can be derived from formula (5). In the ANP with a (n × n) super-matrix, in which any element can influence on another element based on the influence flow from a component/cluster to another component/cluster, or from a component to itself (inner dependency loop), the number of elements influencing on or being influenced by criterion i could be up to n elements. In the fuzzy environment, the comparison ratios $\tilde{a}_{ij}$ are represented by the membership functions that indicate the degree of compatibility/possibility.

Fuzzy FMEA

Failure mode and effects analysis (FMEA) is a risk measurement tool, which is used in various engineering and management problems such as project risk management. Accordingly, a risk priority number (RPN) is constructed for measuring key risk elements and prioritizes several risky problems/projects, for which the largest RPN corresponds to the riskiest problem/project being considered. The purpose of this section is to explain the logic and shortcomings of RPN values.

In the FMEA, risk value is evaluated by grading the data according to key risk elements: 1) severity of effect (S), 2) frequency of occurrence (P), and 3) detectability (D). The multiplied sum of these figures produces the risk priority number. Failure mode and effects analysis extends the risk priority matrix that includes RPN for each project:

$$\mathrm{RPN} = \mathrm{Severity} \times \mathrm{Probability} \times \mathrm{Detection} \tag{6}$$

In typical RPN problems, a rating of 1 to 10 on each scale will be assigned to each risk element, with 10 being severe, very likely to occur, and impossible to detect. These ratings are then multiplied together to obtain RPN values, which are used to assess the projects. The idea is that the problem with the highest *RPN* value is the critical one (with a highest priority) that needs to be focused on. However, there are two logical difficulties with calculating the RPN. As argued by Wheeler (2011), multiplication of the RPN elements is nonsense; with having assigned a range of 1 to 10 to each element, RPN varies from 1 to 1,000 with only 125 possible values, which are not uniformly distributed between 1 and 1,000. In the typical RPN, the three elements are assumed to be of the same importance while being given crisp values ranging from 1 to 10. RPN values gained from multiplication of the three elements are not meaningful because each value is an interval scale and not a ratio scale as a requirement for multiplication. However, in a ratio scale, the values can be ordered with consistently identical distance between two values (the distance between 1 and 3 is the same of the distance between 5 and 7, and etc.), and with an absolute zero point (starting from zero rather than 1).

To overcome the shortcomings of using certain value and illogical multiplication, the elements can be considered as linguistic values ranging from Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH) respectively. By using RPN linguistic scores, 125 problem descriptions (5^3) can be obtained; each with the 5 options above e.g. a risk score of HMH (High, Medium High) reflect values of (Severity, Occurrence, Detectability) respectively. So far, all the values for RPN elements are assumed to be crisp ranging in [1,5]. Conversely, the elements can be considered as criteria with fuzzy number as described earlier. Therefore, the fuzzy range of ($\hat{1}, \hat{3}, \hat{5}, \hat{7}, \hat{9}$) can be used to express linguistic priorities. Using fuzzy number ranging from $\hat{1}, \hat{3}, \hat{5}, \hat{7}$, to $\hat{9}$, each problem description can be seen as a fuzzy linguistic value, and a ratio fuzzy scale can be achieved by a synthesized fuzzy number. Adopting from the extent analysis (Chang, 1996), the synthesized result for criterion i will remain fuzzy as shown in formula (7).

$$S_i = \sum_{j=1}^{n} \tilde{a}_{ij} \otimes \left(\sum_{i=1}^{n}\sum_{j=1}^{n} \tilde{a}_{ij}\right)^{-1} = (l_{si}, m_{si}, u_{si}); \quad i, j = 1,2,\ldots,n \qquad (7)$$

$$V(M \geq L) = \text{supreme}_{\,x \geq y} \left[\min\ \mu_L(x), \mu_M(y)\right] \qquad (8)$$

Where V is the possibility of $M \geq L$ and a pair (x,y) exists, If $x \geq y$ and $\mu_L(x) = \mu_M(y) = 1$, then $V(M \geq L) = 1$ where V is the possibility distribution. Considering M and L are convex fuzzy numbers (l, m, u) and L= (1,3,5) and M= (3,5,7):

$$V(M \geq L) = 1 \quad \text{as } m_M = 5 \text{ and } \geq m_L = 3 \qquad (9)$$

$$V(L \geq M) = \mu_L(d) = D = 0.5 \qquad (10)$$

D is equal to μ (d), and d is the intersection point of two sides of triangles of fuzzy number M and L.

we have:

Line 1: p1: (5,0), p2: (3,1) then (Y-0)/(1-0) = (X- 5)/(3-5) then - 2Y= X- 5 (11)

Line 2: p1: (3,0), p2: (5,1) then (Y-0)/(1-0) = (X- 3)/(5-3) then 2Y = X- 3 (12)

Value ‘d’ can be found by equalizing the simultaneous equations by adding equations for Line 1 and line 2, therefore:

0 =2X- 8, then X = 4 so, d =4, and therefore by substituting d in Line 1 or Line 2:

Y = D= 0.5, therefore:

$V(L \geq M) = 0.5$

Interestingly, the degree possibility for M ≥ L equals 1 whereas it is 0.5 for L ≥ M.

We also have:

$$V(L \geq M, H, VH)= V(\hat{1} \geq \hat{3} \text{ and } \hat{5} \text{ and } \hat{7} \text{ and } \hat{9}) = \text{Min } (V(L \geq M) , V(L \geq H) \text{ and } V(L \geq VH)= V(L \geq M)= V(\hat{1} \geq \hat{3}) = 0 \quad (13)$$

That means the fuzzy number $\hat{1}$ (Low) cannot be greater than fuzzy values (M, H, VH) at once as the degree possibility is zero.

The synthesized fuzzy number for caparison matrix $\tilde{A}$ can be derived using formula (14):

$$\text{Fuzzy RPN} = \text{Fuzzy Severity (S)} * \text{Fuzzy Occurrence (P)} * \text{Fuzzy Detection (D)} \quad (14)$$

To avoid the logical failure of the multiplication of the three risk elements Severity (S), Occurrence (P), and Detection (D) in obtaining RPN the linguistic scales can be replaced for ranking projects with regards to their risks and the impacts. As shown in **Table 2**, the risk values can be classified to 5 fuzzy numbers which reflect the linguistic scales with fuzzy range possibility for each scale. By ordering of these three risk aspects, a fuzzy RPN value for each project with combination of three fuzzy numbers for three risk elements is allocated. All the possible combinations will be 125 (= 5*5*5) with different scores which can be ordered based on their centred average in a descending order to see the most critical (risky) projects at the top of the table. In this approach, equal importance is given to each risk element.

The final rating will range from extremely high (EXH), very high (VH), high (H), medium (M), low (L) and very low (VL). The combinations of the three elements in a descending order from EXH, VH, to H are presented in Appendix 1**.** combinations from 125 possible combinations are ranked from H to EXH. The same combination of elements is defined for medium (M), low (L) and very low (VL). The table presented in Appendix 1 facilitates the collection of data related to pair-wise comparison of risks factors and sub-factors from the group of experts and decision makers.

Evaluation based on distance from average solution (EDAS) method

In order to solve the MCDM problems, the alternatives must be ranked by computing the distance of the possible solutions from the ideal and worst solutions using the EDAS tool (Ghorabaee et al. 2015). The most preferred alternative will have the lowest distance from ideal solution and the highest distance from the nadir solution in VIKOR and TOPSIS methods (Yazdani and Payam, 2015). However, in the proposed approach, the best alternative is related to the distance from the average solution (*AV*). This method does not need to calculate the ideal and the nadir solution, instead two measures dealing with the desirability of the alternatives will be computed. The first measure is the positive distance from average (PDA), and the second is the negative distance from average (NDA). These measures can illustrate the difference between each solution (alternative) and the average solution. As suggested by Ghorabaee et al. (2016), the evaluation of alternatives is made according to the higher values of PDA and lower values of NDA.

<< Insert Table 2 about here >>

The EDAS ranking score can be obtained as follows (Ghorabaee et al. (2016):

Step 1 – Select the most relevant attributes, which describe the alternatives for the specific decision problem.

Step 2 - Let x_{ij} be the performance rating of i^{th} alternative $A_1, A_2, ..., A_n, (i = 1,2,...., n)$ with respect to the j^{th} criterion $C_1, C_2, ..., C_m$ $(j = 1,2,..., m)$. Form the interval decision matrix X and weight of each criterion W as follows:

$$X = [x_{ij}]_{n \times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \tag{15}$$

$$W = [w_1, w_2, ..., w_m]$$

For $(i = 1,2,...., n)$ and $(j = 1,2,..., m)$

where w_j is the weight of criterion j^{th}

Step 3 - The average solution with respect to all criteria must be determined as shown following the formula:

$$AV_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}; \tag{16}$$

Step 4 - The positive distance from average (*PDA*) and the negative distance from average (*NDA*) matrices can be calculated as:

$$PDA_{ij} = \frac{\max(0, (x_{ij} - AV_j))}{AV_j} \tag{17}$$

$$NDA_{ij} = \frac{\max(0, (AV_j - x_{ij}))}{AV_j} \tag{18}$$

In this way PDA_{ij} and NDA_{ij} represent the positive and negative distance of the i^{th} alternative from the average solution in terms of the j^{th} criterion for the lower level of decision matrix, respectively.

Step 5 – Compute the weighted summation of the positive and negative distances from the average matrix:

$$SP_i = \sum_{j=1}^{m} w_j PDA_{ij} \tag{19}$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij} \tag{20}$$

Step 6 – Find the normalized values of SP_i and SN_i for all alternatives as follows:

$$NSP_i = \frac{SP_i}{Max_i(SP_i)} \tag{21}$$

$$NSN_i = 1 - \frac{SN_i}{Max_i(SN_i)} \tag{22}$$

Step 7 – Calculate the appraisal score AS for all alternatives as:

$$AS = \frac{1}{2}(NSP_i + NSN_i), \tag{23}$$

where $0 \le AS \le 1$

Step 8 - Rank the alternatives according to the decreasing values of the appraisal score (AS). The alternative with the highest AS is the best choice.

Problem context and proposed approach

Projects' failure could be the result of poor planning of risk management and a lack of proper risk analysis (Kerzner, 2001). On the other hand, risk management could be seen as a cost-containment tool rather than a systematic process and technique for handling various aspects of the projects (Zwikael and Globerson, 2006). It has been shown that risk management incorporates cost, time, quality and scope are unavoidably connected and interdependent (Lavender 2013, Mantel et al. 2011; Chan et al. 2004). Therefore, if the risk management is considered for controlling cost, then it is similarly concerned with controlling time, quality and scope that could result in successful project delivery.

In the past, clients or contractors rarely formally requested risk analysis for their projects (even for infrastructural projects) (Akintoye and MacLeod 1997). An independent investigation undertaken by

British Airports Authority (BAA) indicates that any UK construction project with over £1 billion in value for construction over 10 years, in addition to all international airport projects completed in the previous 15 years, had not been delivered on time, on budget, safely or met their specified quality standards (Lowe 2013). Due competitive environment for contracting projects, customers are now able to get involved with project, insisting contractors to assume higher levels of risk through various types of contracts: Lump sum, Guaranteed Maximum Price (GMP), or Not-To-Exceed price (NTE). With increasing project size, complexity and competition, the management of risks, particularly at the early stage of the project is becoming an ever more important challenge (Maytorena et al. 2007). Therefore, it is crucial to improve both organizational and project performance with developing risk assessment methodologies that can be mutually accepted as a critical component of successful project delivery (PwC, 2013; KPMG and PMI 2012).

The proposed model integrates analytical network process (ANP) and, failure mode and effect analysis (FMEA) with fuzzy approach in order to develop a meaningful and practical solution to the project risk evaluation problem. These three methods have been integrated to complete three tasks: ANP to weight decision criteria, FMEA to shape the performance-rating matrix (decision table), and the outputs of these two methods are used as input to EDAS (third method) which produces the ranking of the projects considering the risk factors. Each method has its particular advantage, and the intelligent integration of them provides a robust methodology for risk evaluation.

The proposed model to evaluate construction projects based on risk variables can be presented in three phases (**Figure 1**):

Phase I - In the first phase, a team of experts will define the risk attributes, decision alternatives and level of complexity. In this phase, the proposed integrated model will be explained to the experts.

Phase II - The second phase based on the ANP principles represents the relationship and interaction among the decision variables and constructs the pairwise comparison matrix (shown in **Figure 2**). The fuzzy ANP utilizes this matrix to estimate weights of the decision factors and sub-factors. Further in this phase, the initial risk matrix for alternative projects is decided through a new fuzzy FMEA scoring,. Three decision makers (DMs) present their views over projects considering risk determination values. The fuzzy FMEA procedure is explained earlier in the paper. The outputs of this phase will be the input (weights of the attributes and performance rating of projects) of phase III.

<< Insert Figure 1 about here >>

Phase III - At last, in the third phase, the EDAS method (as described earlier) evaluates projects and ranks them from the best to worst. Comparisons with other MCDM methods and sensitivity analysis are performed in order to test the consistency and stability of the results.

Implementation of the proposed approach

In this section, the implementation process of the proposed approach is discussed. Six projects considered in this study are medium to large scale construction projects. These projects are related to building water reservoirs and dams in one of the European countries. Due to the lack of rain and decreasing water resources, the need to construct water reservoirs and dams to improve water availability for agriculture is one of the important issues in this country. All of these projects are from different regions of the country with varying degree of resources availability, weather conditions, geographical features and political situations. Assessing and measuring the risks in developing these construction projects are vital for the successful completion of the projects. Also for planning purpose, it is important to understand the risks involved due to limited resources available for these projects. The risk evaluation of these construction projects in this study is based on measuring the risks with the help of the proposed decision analysis model and then rate them according to different risk parameters. The proposed approach is implemented in consultation with the practitioners and planners to understand the real -life challenges in risk evaluation of constructions projects.

<< *Insert Figure 2 about here* >>

Phase I - This study examines the hierarchical risk breakdown structure (RBS) for risk assessment of construction projects. Organizations use RBS in conjunction with Work Breakdown Structure (WBS) to help management team and eventually analyze risks (Mantel et al. 2011). For the six construction projects, specific risks must be identified and analyzed. In this phase, ANP tool is used to produce the weights of risk factors and sub factors. ANP is an applied tool in MCDM which considers the inter-relationship among risk elements using pairwise comparison. The ANP network (**Figure 2)** presents the criteria and sub-criteria for the risk assessment of the construction projects. Different decision variables for risk evaluation in construction projects are identified based on past literature such as Antuchevičiene et al. (2010) and Zavadskas et al. 2010). However, these factors and sub-factors are later verified during the interviews with the key decision makers in the construction projects. The risk factors in this study are classified into three groups : a) *Technical*, b) *External* and c) *internal* / *organisational* risk factors. The *technical* factors include: C_1) construction requirements; C_2) technology; C_3) complexity and interfaces; C_4) quality and C_5) cost; *external* factors include C_6) subcontractors and suppliers; C_7) economic and market; C_8) weather; and C_9) political; and *internal* factors include C_{10}) resources; C_{11}) funding; and C_{12}) project site.

Later on, the pairwise comparisons among different decision factors and sub-factors are performed, which help to get global weighs of each factors and sub-factors to decide the final risk assessment of the projects. The project risk ratings are determined using fuzzy linguistic variables.

Phase II - In order to obtain the weights of factors and sub-factors using ANP, the pairwise comparison matrix must be performed between factors and sub-factors. To shape the global weight matrix for all the factors, primarily pairwise comparison must be made between each factor and sub-factors based on the defined inter-dependency.

For the FMEA process, three experts / decision makers (DM) deliver their judgments for six projects regarding each decision variable. These decision makers were selected based on their wide experience in manging large scale construction projects. The decision makers selected for this study for providing pairwise comparison of different risk factors and sub-factors have more than 20 years of working experience. **Appendix 1** shows the fuzzy FMEA pre-defined values (FMEA reference rating scales). In this phase the experts carefully consider probability, severity and number of detection parameters using fuzzy linguistic variables. For example DM_1 explains for project 1 corresponding C_2 the severity (S), probability of happening (O) and detection are (1,1,3), (3,5,7) and (1,1,3), respectively. **Appendix 2** presents the information of projects expressed by decision experts. Then linguistic variables are translated to fuzzy values and also the defuzzification process is established.

With the help of the decision makers, pairwise comparisons are performed for the three factors to find independent weights of factors (shown in **Table 3)**. To design Table 3, experts are asked to compare three factors to realize their influence. This task is done using reference scales in Table 1. After that comparison between each factor is performed with regard to the single factor. Table 3 is developed based on the experts' judgment over the importance of different risk factors. For example, as the external factors were identified 5 times more important than technical factors. Therefore, the priority of technical factors over external are 0.2 times. After the pair wise comparison of each factor, sum of each column is obtained. Then, each element is divided by the sum of the column. Finally, average of each raw produces the weights which are seen in the last column. Similar process is followed for each pairwise matrix of the decision variables.

<< Insert Table 3 about here >>

In ANP, when decision system contains factors and sub-factors, pairwise comparisons must be performed in order to find importance (weight) of one over another. The weight of different factors are obtained through multiplication of factors inter-dependence vector and the vector of factors interrelationship with respect to each one. As there are three key decision factors (Technical, External, and Internal) in this study, four vectors (one for inter dependence and one each for three factors) should be multiplied to calculate the final weight of the factor (as shown in equation 24).

$$w_{factors} = \begin{bmatrix} 0.667 & 0.245 & 0.525 \\ 0.15 & 0.428 & 0.334 \\ 0.183 & 0.327 & 0.142 \end{bmatrix} \times \begin{bmatrix} 0.102 \\ 0.686 \\ 0.211 \end{bmatrix} = \begin{bmatrix} 0.347 \\ 0.38 \\ 0.273 \end{bmatrix} \qquad (24)$$

Similarly, the pair-wise comparison of 12 sub-factors are performed to find the local-weight of each sub-factor. It is then multiplied to the weight of the corresponding risk factor (Technical, External, or Internal - as calculated in equation 24) to generate the global weights of each sub-factors. Finally, the normalised weights of each sub-factor are presented in Table 4. The normalized global weights of sub-factors are utilized in the project evaluation process by EDAS in Phase III. EDAS needs the weights of decision factors and sub-factors to find the final ranking of the projects.

<< Insert Table 4 about here >>

Phase III - This section ranks projects using the EDAS method. The aggregated defuzzified matrix (Appendix 3) is used as the initial decision matrix for the EDAS method. The process of ranking alternative projects using EDAS first involves developing the positive distance from average (PDA) and negative distance from average (NDA) matrices as described in equation 17 and 18 (See Appendix 4). Then, the weighted summation of the positive distance (SP) and negative distance (SN) from the average matrix are obtained (as shown in equation 19 and 20). Further, the normalised values of SP and SN for all alternatives (NSP and NSN) are calculated. Finally the appraisal scores (AS) of each alternative are computed according to equation 23. The project with highest appraisal score is considered as the riskiest project. The summary results obtained by the EDAS method and the ranking of the projects are presented in **Table 5**.

<< Insert Table 5 about here >>

The ranking of projects based on EDAS shows this arrangement:

Project 4 > Project 6 > Project 1 > Project 3 > Project 5 > Project 2

Therefore, it is observed that project 4 is the riskiest project based on the judgments of experts and corresponding risk factors. Project 2 is considered as the least risky project among all. It is observed Appendix 3), that Project 4 has the maximum value regarding the criteria "subcontractors and suppliers" (C_6) which is the most important criterion among all. Also, this project has considered as one of the low cost project among others. The results are confirmed through observing the initial data. In this phase, to check the consistency and the accuracy of the obtained ranking outcomes, a comparison of the proposed approach with other popular methods is conducted. EDAS ranking scores are compared with other MCDM tools such as SAW, TOPSIS, VIKOR, COPRAS and WASPAS. The consistency of the proposed method is evident among the ranking orders of the different methods. **Table 6** shows the comparative results, and tests the stability of the model.

<< Insert Table 6 about here >>

Further, sensitivity analysis is conducted on the decision parameters to study the changes in the ranking of the projects. To conduct the sensitivity analysis, relative preferences of experts over the risk factors and sub-factors are altered and weights of decision variables are replaced by random weights. The performance of proposed approach has been then compared and analyzed for each scenario. Each scenario is represented by a ¨set¨ of alternative sub-factors weights. In total, 12 sets of weights are generated to analyze the impact on project ranking (as shown in figure 3). **Table 7** shows the weight replacement scenarios for six projects with respect to the decision variables. Figure 3 shows that significant changes were observed in the ranking orders of the projects. Based on the sensitivity analysis outcomes, it could be concluded that on average, Project 1, Project 4, and Project 6 are the top 3 riskiest projects.

<< Insert Table 7 about here >>

<< Insert Figure 3 about here >>

Discussion

The approach proposed for the risk evaluation of projects in this study embraces multi-level internal, external and organizational factors. The proposed decision framework can help to provide suggestions and improvements for practitioners to improve their decision making capabilities. Generally the interrelationships among different levels of project evaluation are not considered by project managers. This partially blocks the decision-making process from its most accurate route and enhances the complexity of the computations. This paper essentially insists on the importance of taking into consideration such interrelationships and shows how it can be done though utilizing ANP. The proposed approach offers the additional opportunity for practitioners to express their comparisons using fuzzy linguistic values with ANP.

This paper introduces a new FMEA structure utilizing fuzzy linguistic variables. The paper argues that this novel pattern offers a unique anatomy, which increases judgment's preciseness and facilitates efficient decision-making procedure. The FMEA rating classification easily converts solid fuzzy values to the meaningful and informative codes that are exhibited in **Appendix 1**. Moreover, it gives reliable combination of fuzzy scales to constant alarm codes (EXH as extremely high, VH as very high). This will decrease the complexity of the judging process and allow the DM to perform a better analysis of the existing project.

Conclusion and future research direction

Project risk management is increasingly becoming challenging due to the number of variables and parameters with quantitative and qualitative characteristics. Uncertainty and impreciseness have emerged as influential factors at the core of risk evaluation computations. Mitigating complexity, interrelationship and transaction among risk variables is a serious concern for project managers. In this paper, a new integrated model of combining FANP and FMEA in a fuzzy decision-making environment has been proposed to evaluate the potential risks of projects considering internal / organizational, external and technical factors. The ANP with fuzzy linguistic scales is applied in order to obtain relative weights of the sub-criteria and to resolve internal dependencies. In addition, failure mode and effect analysis (FMEA) has been conducted to comprehensively measure fundamental factors such as the likelihood, severity and detection of potential risk for each project. Explaining and rating these factors by verbal codes is crucial. Therefore, the utilization of fuzzy linguistic scales is appropriate to deal with such vagueness and uncertainty in comparing the priority of variables. The proposed FMEA coding improves the decision process and increases the flexibility and efficiency of risk evaluation. In this paper, decision makers offered their opinions regarding FMEA codes and then through defuzzification process, the consequences assessed by them provided the main decision matrix for MCDM process. The proposed framework provides a robust decision-making tool which can aid project managers and investors to analyze different risk factors in multiple levels of a project.

The paper contributes in developing the body of knowledge in MCDM field. A new feature is the integration of the EDAS method in to the risk evaluation process – something that was not considered in past studies. However, the study is highly reliant on the experts' opinions over the priority of the decision variables. Depending on the dimensions and levels of decision, a large pairwise comparison needs to be carried out and, in such cases; fatigue is a serious concern that may cause some reliability issues. In this situation, involving more decision makers in the research could be advantageous.

The proposed integrated MCDM model for risk evaluation can be applied to other decision-making problems such as supply chain risk assessment, productivity and ergonomic risk evaluation in human resource management studies. Although, ANP is a method which analyzes the interactions among decision variables, it cannot recognize the direction of that interaction. In order to tackle that shortcoming future research could expand the scope of this study by addressing the inter-relationships among the criteria using Decision Making Trial and Evaluation Laboratory (DEMATEL) or interpretive structural modeling (ISM) (Hashemi et al. 2015). Another potential improvement in the project evaluation exercise could be the consideration of the risk of investment and, the satisfaction of stakeholders and external customers. Integration of MCDM methods with Quality Function Deployment (QFD) could be considered in future research to address this issue. Moreover, due to the increasing awareness of environmental and social issues, incorporating ecological and sustainability factors in the risk measurement model could be included in the proposed model.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request.

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List of Figures

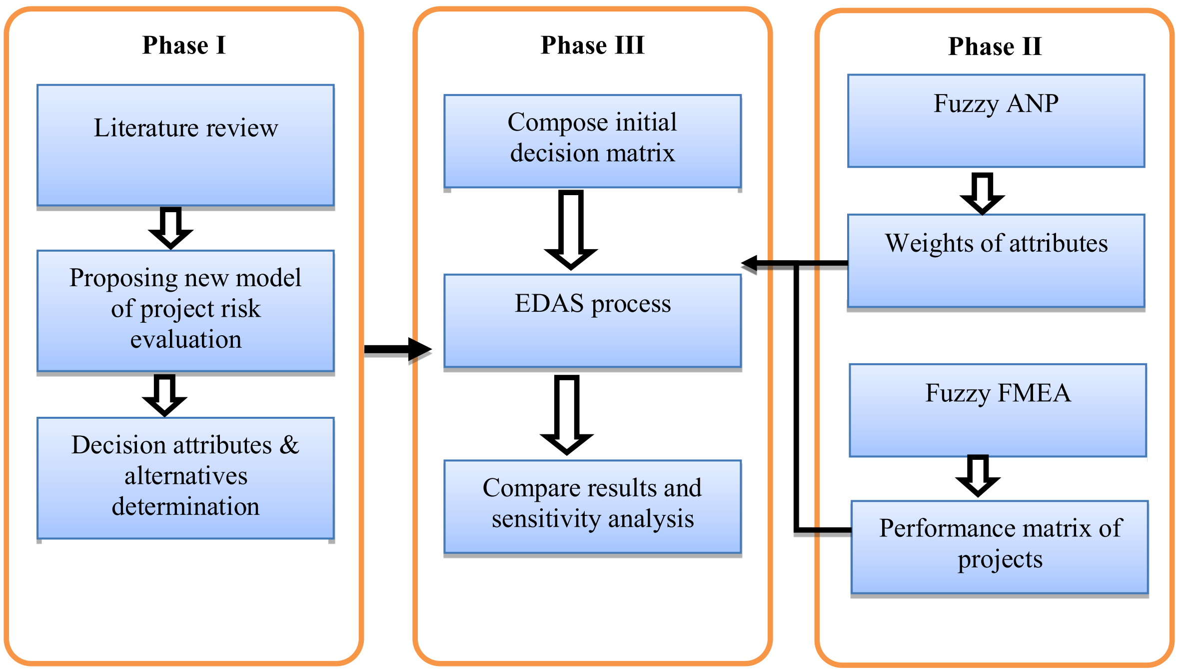

Figure 1. Three phase MCDM model for project risk evaluation problem

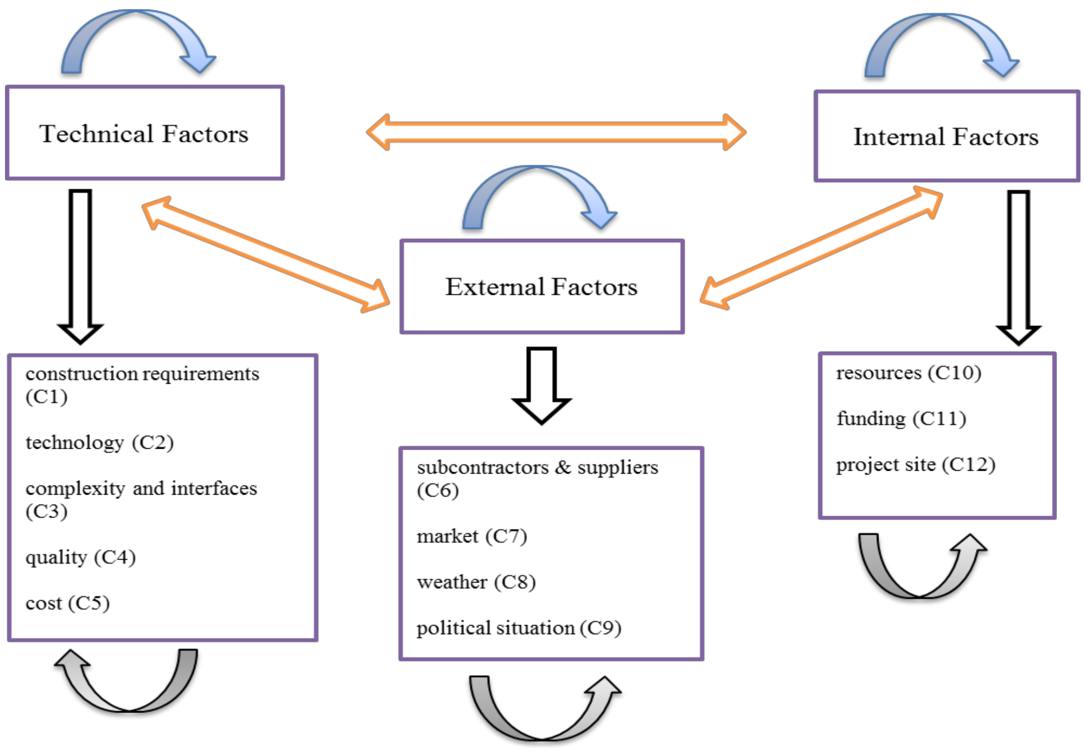

Figure 2. Risk factors and sub-factors relationship and network diagram for ANP

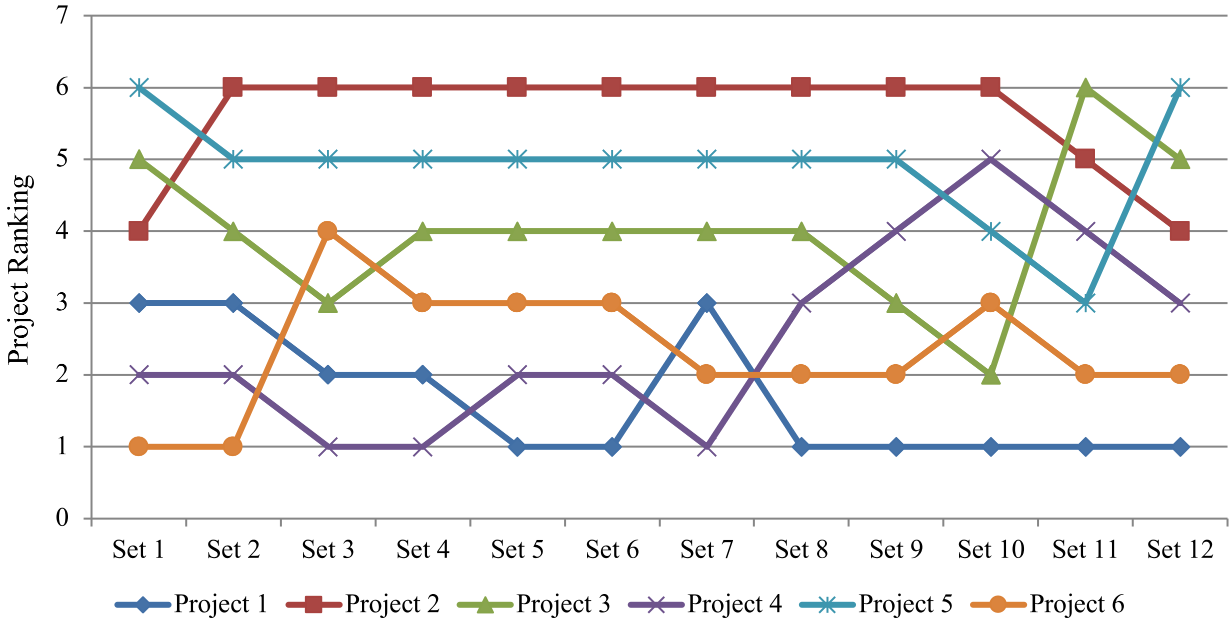

Figure 3. EDAS ranking outcomes based on different scenarios of sensitivity analysis

Table 1. Fuzzy scale for pairwise comparisons

Fuzzy number	Linguistic variables	Triangular fuzzy number
$\tilde{9}$	Extremely important/preferred	(7,9,9)
$\tilde{7}$	Very strongly important/preferred	(5,7,9)
$\tilde{5}$	Strongly important/preferred	(3,5,7)
$\tilde{3}$	Moderately important/preferred	(1,3,5)
$\tilde{1}$	Equally important/preferred	(1,1,3)

Table 2. Classification of fuzzy linguistic variables for RPN scoring

Linguistic Term	Fuzzy Number	Severity	Occurrence	Detection
Very Low	$\hat{1}$	A failure that has no/ minor effect on the system performance, the operator probably will not notice.	It would be very unlikely for these failures to be observed.	Defect remains undetected until the system performance degrades to the extent that the task will not be completed.
Low	$\hat{3}$	A failure that would cause slight annoyance to the operator, but that cause no deterioration to the system.	Likely to occur once, but unlikely to occur more frequently.	Defect remains undetected until system performance is severely reduced.
Medium	$\hat{5}$	A failure that would cause a high degree of operator dissatisfaction or that causes noticeable but slight deterioration in system performance.	Likely to occur more than once.	Defect remains undetected until system performance is affected.
High	$\hat{7}$	A failure that causes significant deterioration in system performance and/or leads to minor injuries.	Near certain to occur at least once.	Defect remains undetected until an inspection/test is carried out.
Very High	$\hat{9}$	A failure that would seriously affect the ability to complete The task or cause damage, serious injury or death.	Almost certain to occur several times.	Failure remains undetected, until a full inspection and test is completed.

Table 3. Pairwise comparison matrix for decision variables

Comparative rating of all factors							
Factors	**Technical**	**External**	**Internal**				**weight**
Technical	1	0.2	0.33	0.1111	0.1429	0.0526	0.102
External	5	1	5	0.5556	0.7143	0.7895	0.686
Internal	3	0.2	1	0.3333	0.1429	0.1579	0.211
	9	1.4	6.3				
Relative importance of all factors with respect to technical factor							
Technical	Technical	External	Internal				weight
Technical	1	3	7	0.6774	0.5	0.8235	0.667
External	0.33	1	0.5	0.2258	0.1667	0.0588	0.150
Internal	0.14	2	1	0.0968	0.3333	0.1176	0.183
	1.48	6	8.5				
Relative importance of all factors with respect to external factor							
External	Technical	External	Internal				weight
Technical	1	0.14	2	0.1176	0.0455	0.5714	0.245
External	7	1	0.5	0.8235	0.3182	0.1429	0.428
Internal	0.5	2	1	0.0588	0.6364	0.2857	0.327
	8.5	3.1	3.5				
Relative importance of all factors with respect to internal factor							
Internal	Technical	External	Internal				weight
Technical	1	2	3	0.5455	0.6	0.4286	0.525
External	0.5	1	3	0.2727	0.3	0.4286	0.334
Internal	0.33	0.33	1	0.1818	0.1	0.1429	0.142
	1.8	3.3	7				

Table 4. ANP global weights assigned for each sub-factors

Factors	**Sub-factors (Indicators)**	**Sub-factors local weight**	**Factors weight**	**Sub-factors global weights**	**Normalized global weight**
Technical	construction requirements (C_1)	0.0621		0.0215	0.063
	technology (C_2)	0.1093	**0.347**	0.0379	0.11
	complexity and interfaces (C_3)	0.0867		0.0301	0.088
	quality (C_4)	0.0446		0.0155	0.045
	cost (C_5)	0.0599		0.0208	0.061
External	subcontractors & suppliers (C_6)	0.1235		0.0469	0.137
	market (C_7)	0.1067	**0.380**	0.0405	0.118
	weather (C_8)	0.1006		0.0382	0.111
	political situation (C_9)	0.0774		0.0294	0.086
Internal	resources (C_{10})	0.0736		0.0201	0.058
	funding (C_{11})	0.0963	**0.273**	0.0263	0.077
	project site (C_{12})	0.0594		0.0162	0.047

Table 5. Ranking of projects based on EDAS method

	SP	SN	NSP	NSN	AS	RANK
Project 1	0.514	0.366	0.891	0.477	0.684	3
Project 2	0.200	0.699	0.347	0	0.174	6
Project 3	0.317	0.377	0.549	0.461	0.505	4
Project 4	0.576	0.294	1	0.580	0.790	1
Project 5	0.320	0.406	0.555	0.420	0.487	5
Project 6	0.525	0.310	0.911	0.557	0.734	2

Table 6. Comparison of other MCDM techniques with EDAS

	SAW	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
Project 1	3	3	3	3	4	3
Project 2	6	6	6	6	6	6
Project 3	4	4	4	5	5	4
Project 4	1	1	1	1	1	1
Project 5	5	5	5	4	3	5
Project 6	2	2	2	2	2	2

Table 7. Twelve scenarios for sensitivity analysis

Scenarios	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Set 1	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366
Set 2	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045
Set 3	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472
Set 4	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585
Set 5	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605
Set 6	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627
Set 7	0.0856	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765
Set 8	0.0877	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856
Set 9	0.1104	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877
Set 10	0.1113	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104
Set 11	0.1179	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113
Set 12	0.1366	0.045	0.0472	0.0585	0.0605	0.0627	0.0765	0.0856	0.0877	0.1104	0.1113	0.1179

Appendices:

Appendix 1: Fuzzy FMEA rating reference for projects and assigned defuzzified values

S	P	D	SPD	Code	Defuzzified Value
(7,9,9)	(7,9,9)	(7,9,9)	(343,729, 729)	EXH1	600.33
(7,9,9)	(5,7,9)	(5,7,9)	(175,441, 729)	EXH2	448.33
(5,7,9)	(7,9,9)	(5,7,9)	(175,441, 729)	EXH2	448.33
(5,7,9)	(5,7,9)	(7,9,9)	(175,441, 729)	EXH2	448.33
(5,7,9)	(5,7,9)	(5,7,9)	(45,343, 729)	EXH3	372.33
(5,7,9)	(3,5,7)	(3,5,7)	(125,175, 441)	VH1	247
(3,5,7)	(5,7,9)	(3,5,7)	(45,175, 441)	VH2	220.33
(3,5,7)	(3,5,7)	(5,7,9)	(45,175, 441)	VH2	220.33
(3,5,7)	(3,5,7)	(3,5,7)	(27,45,343)	H1	138.33
(1,3,5)	(1,3,5)	(3,5,7)	(1,45,175)	H2	74.33
(3,5,7)	(1,3,5)	(1,3,5)	(1,45,175)	H3	73.00
(1,3,5)	(3,5,7)	(1,3,5)	(3,45,175)	H3	73.00
(1,3,5)	(1,3,5)	(1,3,5)	(1,27,125)	M1	51
(7,9,9)	(1,1,3)	(1,1,3)	(7,9,81)	M2	32.33
(1,1,3)	(7,9,9)	(1,1,3)	(7,9,81)	M2	32.33
(1,1,3)	(1,1,3)	(7,9,9)	(7,9,81)	M2	32.33
(3,5,7)	(1,1,3)	(1,1,3)	(3,5,63)	L	23.67
(1,1,3)	(3,5,7)	(1,1,3)	(3,5,63)	L	23.67
(1,1,3)	(1,1,3)	(3,5,7)	(3,5,63)	L	23.67
(1,3,5)	(1,1,3)	(1,1,3)	(1,3,45)	VL1	16.33
(1,1,3)	(1,3,5)	(1,1,3)	(1,3,45)	VL1	16.33
(1,1,3)	(1,1,3)	(1,3,5)	(1,3,45)	VL1	16.33
(1,1,3)	(1,1,3)	(1,1,3)	(1,1,9)	VL2	3.67

Appendix 2: Decision makers rating over risk factors of projects using FMEA codes

DM_1	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**	**C_9**	**C_{10}**	**C_{11}**	**C_{12}**
Project 1	EXH2	L	H3	M2	VL2	L	VH2	M1	L	M1	M2	M2
Project 2	VL1	L	M1	M1	VH1	M1	M2	VL2	VL2	VH2	M1	H2
Project 3	M1	M1	EXH2	L	M2	L	M1	M2	H1	H2	L	L
Project 4	H2	L	M2	H3	L	EXH3	M1	H2	H2	M1	L	M2
Project 5	M2	VH1	M2	L	M2	M1	M2	M1	M1	M1	M1	L
Project 6	L	M2	H1	M1	L	VH2	VL1	H3	L	H3	EXH3	VL2
DM_2												
Project 1	EXH3	L	H2	M1	VL1	VL2	VH1	M2	VL1	M2	M1	M1
Project 2	VL2	VL1	M2	M2	VH1	M1	M1	VL1	VL2	VH1	M1	H1
Project 3	M1	M2	EXH2	L	M1	VL1	M2	M1	H2	H2	VL2	VL1
Project 4	H3	L	M1	H3	VL1	EXH2	M2	H2	H1	M2	VL1	M2
Project 5	M1	VH2	M2	VL2	M1	M2	M1	M2	M1	M2	M2	VL2
Project 6	VL1	M2	H2	M1	L	VH1	VL2	H2	VL1	H2	EXH2	L
DM_3												
Project 1	VH1	VL2	H1	M1	VL1	VL1	VH2	M1	VL2	M1	M1	M2
Project 2	VL1	VL1	M2	M1	VH2	M2	M1	VL1	VL2	VH1	M2	H1
Project 3	M1	M1	EXH3	VL2	M1	VL1	M1	M2	H3	H3	VL2	VL2
Project 4	H2	L	M1	H1	VL2	EXH3	M2	H3	H1	M2	VL2	M2
Project 5	M2	VH1	M1	VL1	M1	M2	M2	M2	M2	M1	M1	VL1
Project 6	VL2	M1	H3	M2	VL1	VH2	VL1	H1	VL2	H2	EXH1	VL1

Appendix 3: Defuzzified aggregated decision makers judgment table (Initial decision matrix)

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Project 1	355.89	17	95.22	44.78	12.11	14.56	229.22	44.78	14.56	44.78	44.78	38.55
Project 2	12.11	18.78	38.55	44.78	238.11	44.78	44.78	12.11	3.67	238.11	44.78	117
Project 3	51	44.78	423	17	44.78	18.78	44.78	38.55	95.22	73.89	10.34	14.56
Project 4	73.89	23.67	44.78	94.78	14.56	397.66	38.55	73.89	117	38.55	14.56	32.33
Project 5	38.55	238.11	38.55	14.56	44.78	38.55	38.55	38.55	44.78	44.78	44.78	14.56
Project 6	14.56	38.55	95.22	44.78	21.22	229.22	12.11	95.22	14.56	73.89	473.66	14.56

Appendix 4: Matrices of the positive distance from average (PDA) and the negative distance from average (NDA)

PDA	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Project 1	2.9109	0	0	0.0307	0.8065	0	2.371	0	0	0	0	0
Project 2	0	0	0	0.0307	0	0	0	0	0	1.7795	0	2.0317
Project 3	0	0	2.4515	0	0.2846	0	0	0	0.9716	0	0	0
Project 4	0	0	0	1.1816	0.7674	2.2089	0	0.4626	1.4225	0	0	0
Project 5	0	2.7508	0	0	0.2846	0	0	0	0	0	0	0
Project 6	0	0	0	0.0307	0.6609	0.8497	0	0.8849	0	0	3.4905	0

NDA	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Project 1	0	0.7322	0.223	0	0	0.8825	0	0.1136	0.6986	0.4773	0.5755	0.001
Project 2	0.8669	0.7042	0.6854	0	2.8041	0.6387	0.3415	0.7603	0.924	0	0.5755	0
Project 3	0.4396	0.2947	0	0.6086	0	0.8485	0.3415	0.2368	0	0.1375	0.902	0.6228
Project 4	0.188	0.6271	0.6346	0	0	0	0.433	0	0	0.55	0.862	0.1623
Project 5	0.5763	0	0.6854	0.6649	0	0.6889	0.433	0.2368	0.0729	0.4773	0.5755	0.6228
Project 6	0.84	0.3927	0.223	0	0	0	0.8219	0	0.6986	0.1375	0	0.6228